

# Introduction to Explainable AI

**Deep Learning Tutorial**

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# 1 xAI in Public Policy

# Motivation: Why XAI?

As technology progresses, transparency is essential for ethical AI deployment.

The core of this idea lies in *human interpretability*:

- “**Interpretability is the degree to which a human can understand the cause of a decision**” (Biran & Cotton, 2017)

We need to interpret the *methods* and *predictions* behind AI models (Molnar, 2025), in order to trust and govern AI systems, especially when deployed in society, such as...

- COMPAS recidivism tool
- Medical triage algorithms
- Automated eligibility systems

**Regulation is catching up:**

- OECD guidelines and the EU AI Act demand clear explanations, bias checks and human oversight for high-risk systems
- Tradeoff: Performance vs Interpretability?

## Case 1: COMPAS recidivism tool

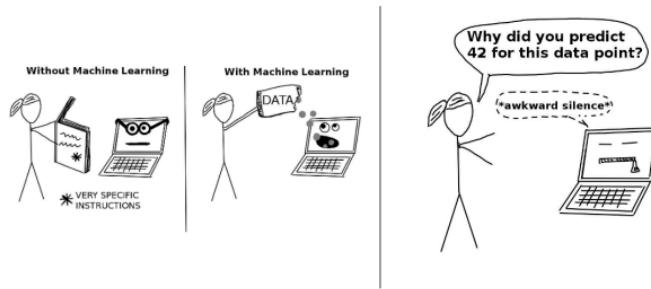
- Correctional Offender Management Profiling for Alternative Sanctions, or COMPAS
- Tool used in U.S. courts to predict likelihood of reoffending
- **Controversy:** Alleged racial bias in predictions
  - A [ProPublica investigation](#) revealed that Black defendants were more likely to be incorrectly labeled as risky, despite not re-offending
- Model was proprietary and opaque
- Highlighted need for transparent and accountable AI-based decision making systems

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Figure 1: Example of Risk Prediction and Recidivism in Florida, source: ProPublica

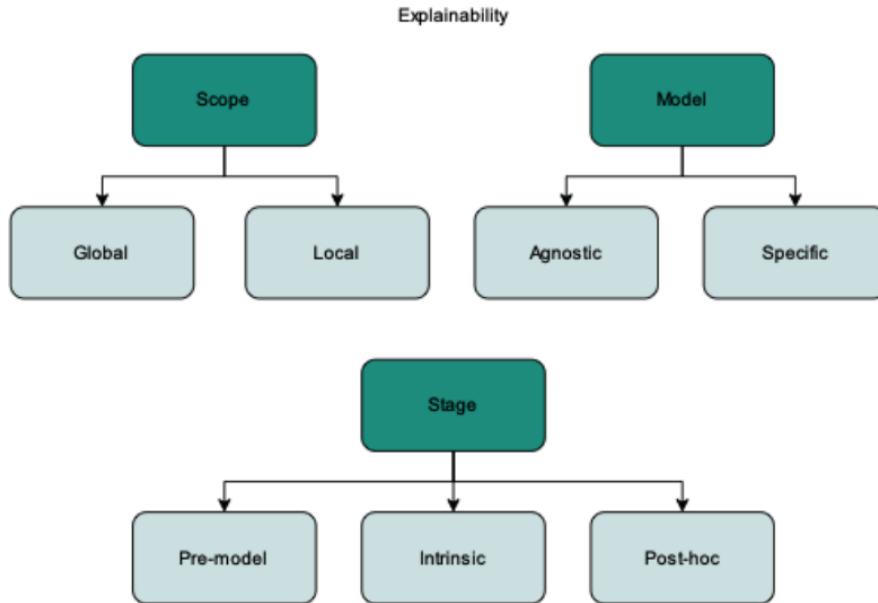
## Case 2: Credit Scoring

- Credit scoring agencies use statistical models to evaluate creditworthiness
- **Controversy:** Lack of transparency in how scores are calculated
  - Consumers are often unaware which factors influence their scores
  - Individuals might be affected in their ability to obtain loans, housing, or employment
- Regulators stress the need for explainability to ensure fairness, prevent discrimination
- **Example:** EU's General Data Protection Regulation (GDPR) includes a "*right to explanation*" for individuals affected by automated decision-making
- ...yet enforcement and practical implementation remain challenging



## **2 Methods**

# Taxonomy



## Our Case

**“I’ve always paid my loans back on time – what’s going on?”**

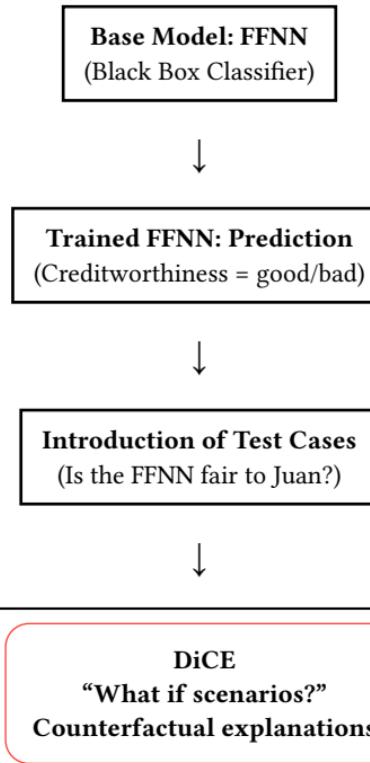


**Meet Juan, a 35-year-old immigrant living in Germany.**

He runs a small bookstore in Pankow, Berlin. Recently, flooding from an adjacent building damaged his shop, so he urgently applied for a loan to repair the property.

On paper, Juan looks like a strong applicant, but his loan gets denied. Can XAI methods tell us where the model failed him?

# Toy Model: FFNN and Methods



## LIME

**“Why was Juan classified as high risk and therefore declined as a credit applicant?”**

### What is LIME?

- Local Interpretable Model-Agnostic Explanations
- Provides selective, local explanations for individual predictions

### Why is it relevant?

- Shows why a single feature drove a specific decision
- Good to zoom in on an individual case and the model’s behavior around that feature

# DiCE

**“What changes in Juan’s feature profile would flip the decision?”**

## What is DiCE?

- Diverse Counterfactual Explanations
- “*What if*” scenario analysis into the features the model treats as most actionable

## Why is it relevant?

- Counterfactuals map the applicant’s profile and make choices more transparent
- Provide a way forward if we were to make model adjustments

# SHAP

**“Which features matter the most overall, across all combinations?”**

## What is SHAP?

- SHapley Additive exPlanations
- If features were players in a *game*, how much would each contribute to the overall payout, or prediction?

## Why is it relevant?

- Provides global, game theory explanations of feature importance
- Detects feature interactions and nonlinearities relevant for deep learning

## 3 Takeaways

## Takeaways

- **At core:** Human interpretability & oversight
  - Explaining both the *model* and the *cause* behind the *prediction*
- One should **prioritize inherently interpretable models whenever possible**
- If performance is critical, **use of black box models should be paired with rigorous evaluation of explainability methods** throughout their application
- Explainability methods are helpful but are limited
  - **One method is not enough** (see local/ global)
  - **Interpretations require caution** (“importance” of what, and in what sense?)
  - We can try to capture uncertainty... but data and efficiency constraints remain

## 4 Q&A

# Acknowledgements

## References

- Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016). Machine bias: There's software used across the country to predict future criminals. And it's biased against Blacks. ProPublica. <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>
- Molnar, C. (2025). Interpretable machine learning: A guide for making black box models explainable (3rd ed.). <https://christophm.github.io/interpretable-ml-book/>

## Template & Images

- typst template by [diatypst](#)
- Bookstore image: provided
- Blackbox image: Molnar, 2025
- Taxonomy figure: <https://transferlab.ai/trainings/explainable-ai/>

## Annex I: LIME

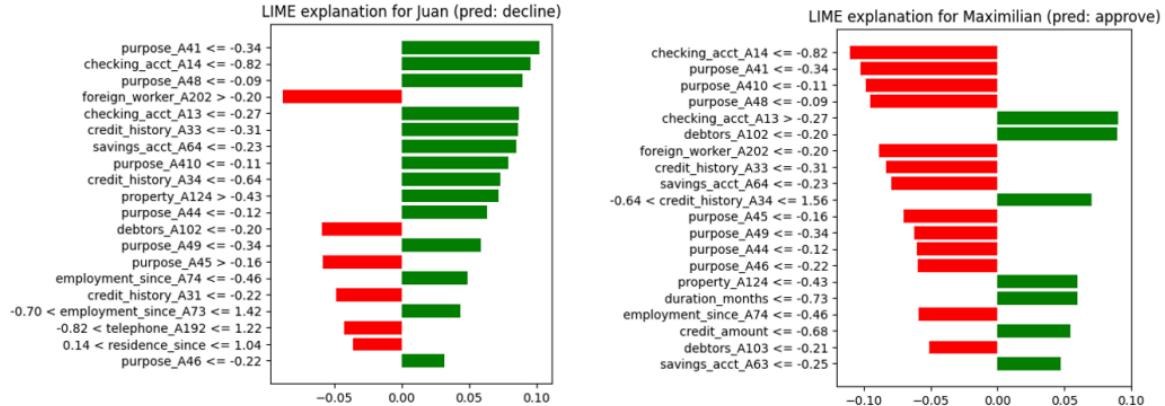


Figure 2: Local Explanations of FFNN Predictions: The Cases of Juan and Maximilian

## Annex II: DiCE

### JUAN'S LOAN APPLICATION

Juan's predicted class: decline

Juan's Application Data:

	duration_months	credit_amount	installment_rate	residence_since	age	existing_credits	maintenance_people	checking_acct_A12	checking_acct_A13	checking_acct_A14
0	14	3000	2	4	35	2	1	1	0	0

What Juan needs to change to get approved:

100% [██████████] 1/1 [00:00<00:00, 5.42it/s]

Found 2 scenario(s) with changes to foreign\_worker, age, credit\_amount, or duration:

Scenario 1:

Columns that need to change:

	credit_amount	foreign_worker_A202
current	3000.0	1.0
scenario_1	11895.7	0.0

Scenario 2:

Columns that need to change:

	duration_months	credit_amount
current	14.0	3000.0
scenario_2	39.6	16411.3

Figure 3: Counterfactual Analysis based on Scenarios 1-3 of Potential Feature Changes

## Annex III: SHAP

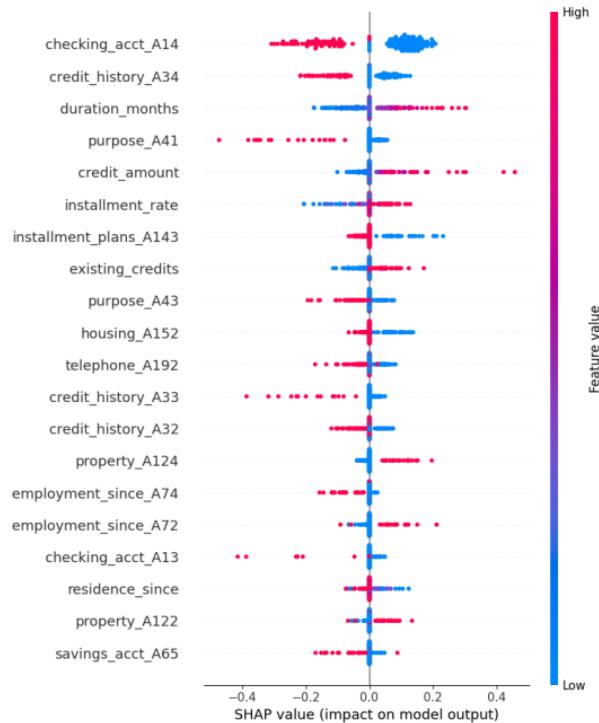


Figure 4: Global Feature Importance Based on SHAP